Re-Engineering Key National Economic Indicators

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Status quo: Decentralized data collections

Real output

- Census collects the “numerator”: Revenue
- BLS collects the “denominator”: Prices
- BEA does the division: Q = P*Q/P

Non-simultaneous collection of price and quantity

- Stratified surveys from small and deteriorating samples
- Mismatch of price and revenue data
- High cost and burden
- Difficulty of accounting for changes in products

Re-engineering measuring sales and prices

Challenge: Tap the firehose of transactions level data now available from businesses on P and Q .

P&Q microdata
- Internet retailers
- Brick and mortar
- Aggregators

Agencies

Data products:
- GDP
- inflation

Data improvements:
- Quality change
- Timeliness
- Granularity
- Distributional statistics

Reengineered data for retail P and Q

Item-level transactions data

- Item-level data allows inferring price from sales and quantities
- Price, quantity and revenue measured
  - Simultaneously
  - At high frequency
  - Universe (or large sample) of transactions
  - With little lag
  - With reduced need for revisions
  - With granular information on location of sale (geography, store/online)
  - Immediate accounting for changes in goods

Re-engineering: Accept data as they come

Alternative modes of data collection should co-exist:

1. Direct collection of item-level transaction

   e.g., Australian Bureau of Statistics received transactions date from chain grocers

2. Firms aggregate transaction data with APIs

   Multiple APIs to accommodate different information systems

3. Aggregators

   Valued-added product: Prepare statistical reports (data feeds) from information already collected from firms

Re-engineering benefits to firms

- Data feed replaces multiple surveys and enumerations
- Data requests match information systems
- Official statistics better matched firm-specific metrics
- Better national economic indicators
- Better evidence on productivity and innovation

Re-engineering challenges

- Company buy-in for reporting item-level data
- Heterogeneity of company information systems
- Stability/consistency of data stream
- Re-engineering: Human, software, and computation/storage
- Organization and coordination of the statistical agencies
- Conceptual and measurement issues (this paper’s topic)

Roadmap of analysis presented today

Using scanner data for P and Q

- Nielsen covers grocery stores and mass merchandisers
  - More than 100 product groups and 1000 product modules.
  - Classify into Food and NonFood items
    - Food nominal expenditures: Compare scanner data to Census surveys and Personal consumption expenditures for food (Scanner provides high frequency product detail)
    - Food and NonFood prices indices: Compare scanner price indices (with and without quality adjustment) to BLS CPI
- NPD covers general merchandise and online retailers
  - NPD data have rich product attributes
  - Explore hedonics vs. alternative methods (e.g., UPI) for quality adjustment

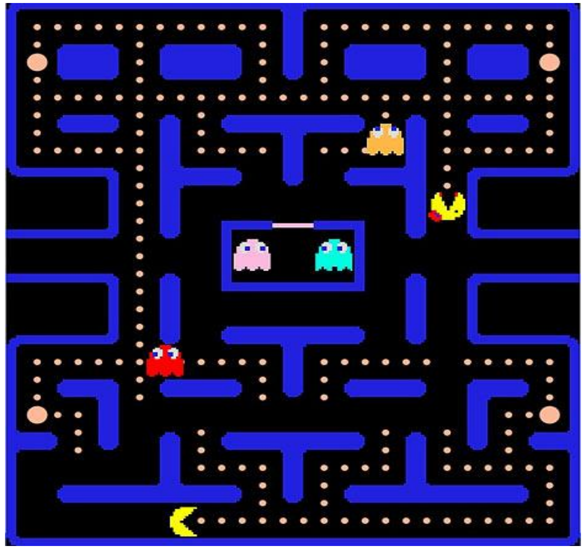
Price indices adjusted for quality

Key challenge/opportunity: Enormous Product Turnover

- 650,000 products per quarter from 35,000 stores
- Product entry and exit rates (quarterly)
  - 9.62% (entry) and 9.57% (exit)
- Sales-weighted entry and exit rates
  - 1.5% (entry) and 0.3% (exit)
  - Rates vary substantially across product groups
  - Asymmetry in sales-weighted: “slow death” of exiting products

Source: Nielsen scanner data (Food and NonFood)

Sorting out product turnover



Some product turnover is mainly packaging and marketing.
Product entry and exit rates
for soft drinks are both 7.1% per quarter.
Sales weighted: 0.3% (entry), 0.07% (exit)

Source: Nielsen scanner data

Some reflects substantial changes in product design.
Product entry and exit rates for video games 12.9% and 13.5% per quarter.
Sales weighted: 30.3% (entry) 0.5% (exit).

Capturing product quality: Alternative approaches

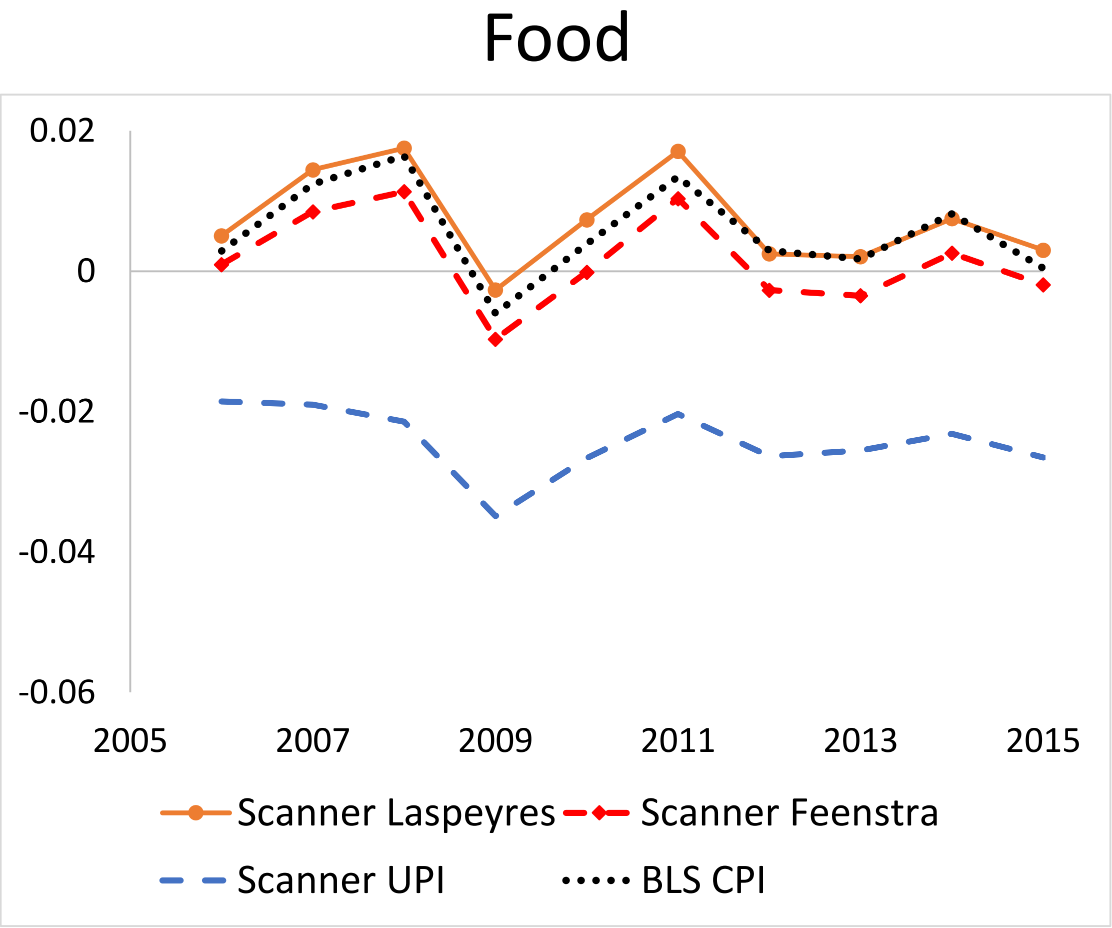
UPI: Expenditure function approach using CES aggregators

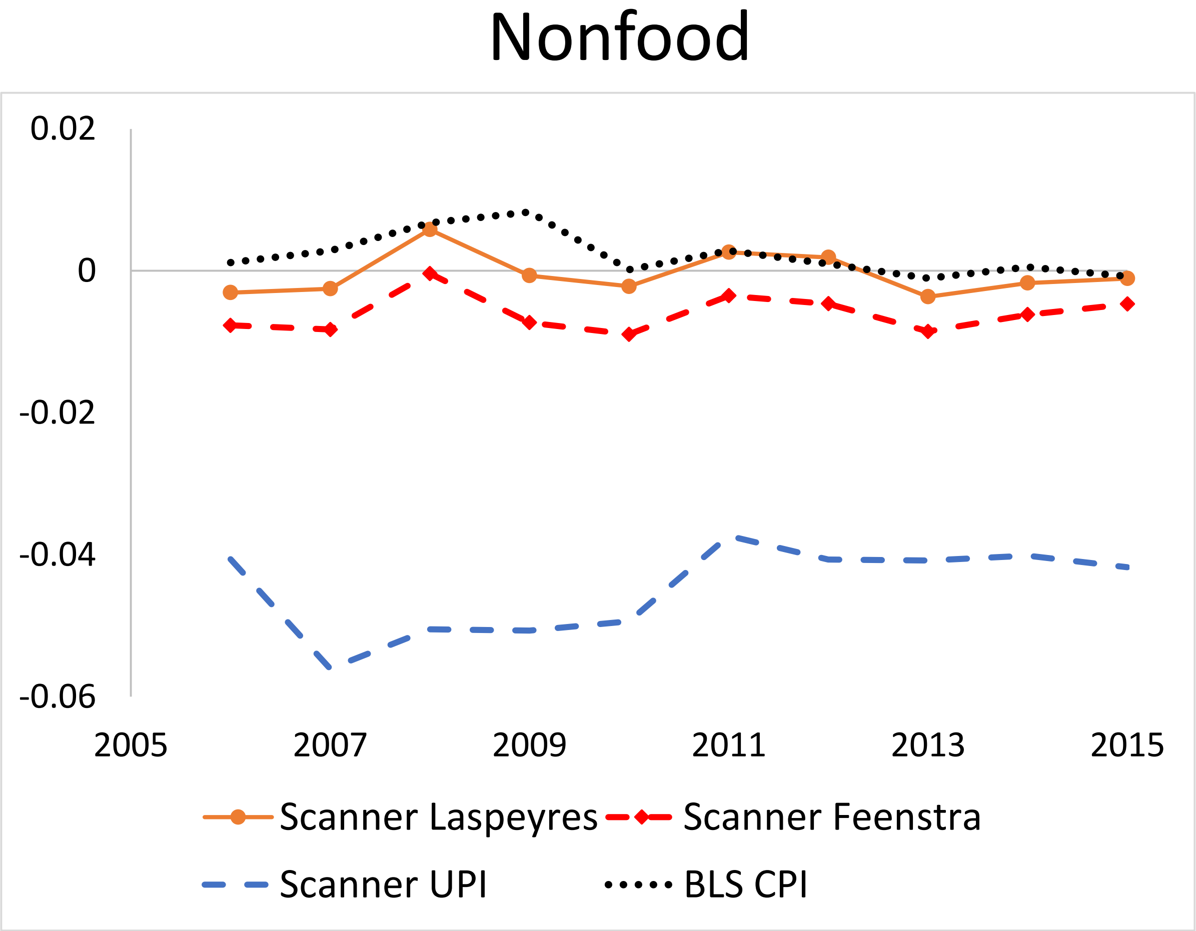
- Capture product turnover with changing expenditure shares of new vs. old goods PV_{adj} (Feenstra 1994)
- Extend to capturing quality/appeal change of existing goods CV_{adj} (Redding-Weinstein 2018)
- *Needs item classification/nesting + estimation of elasticity of substitution*

Hedonic approach

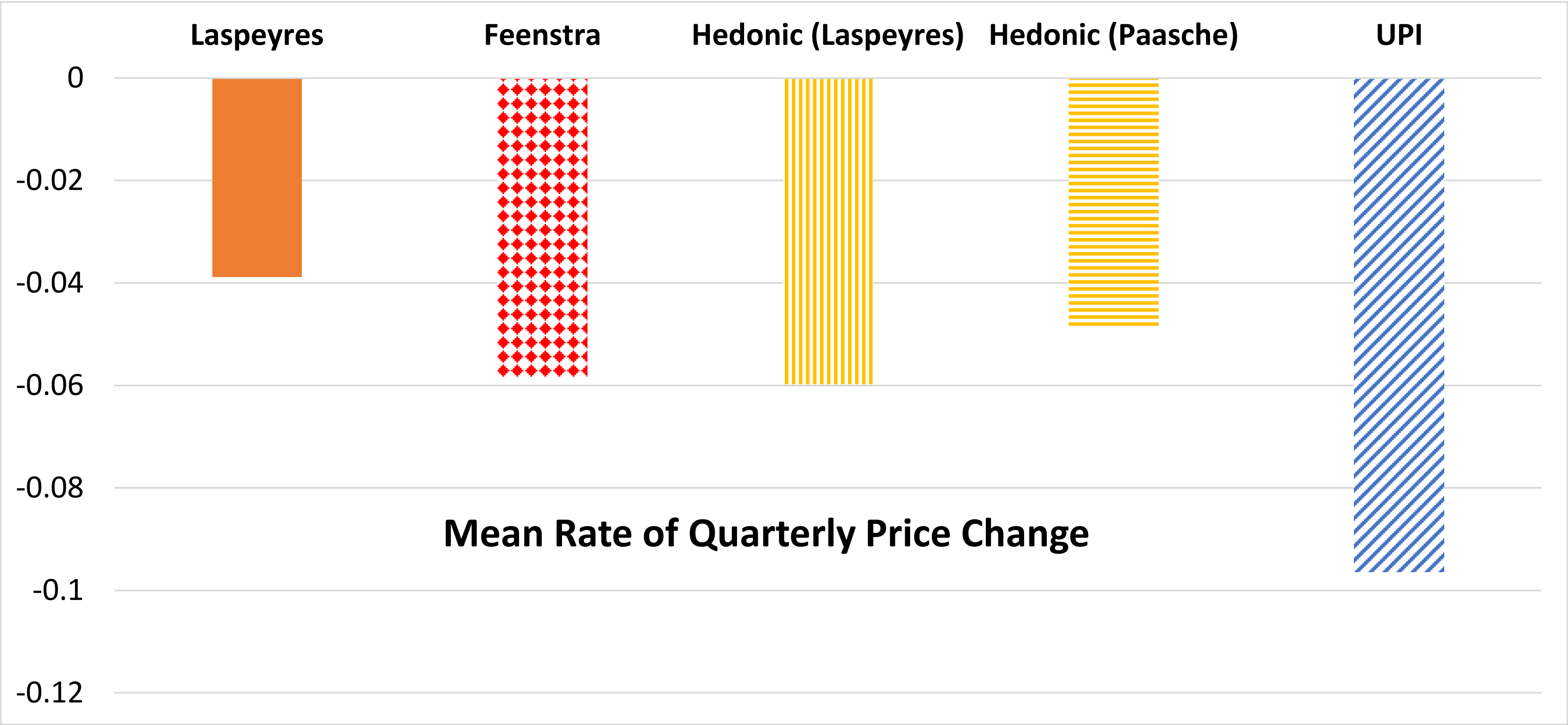
- Estimate hedonic function within product groups using relationship between P and attributes (Pakes 2003)
- Use chain-weighting to accommodate turnover (Bajari and Benkard 2005)
- *Needs item attributes*

Laspeyres index using scanner is similar to BLS CPI (especially food) While Feenstra and UPI have much lower price change





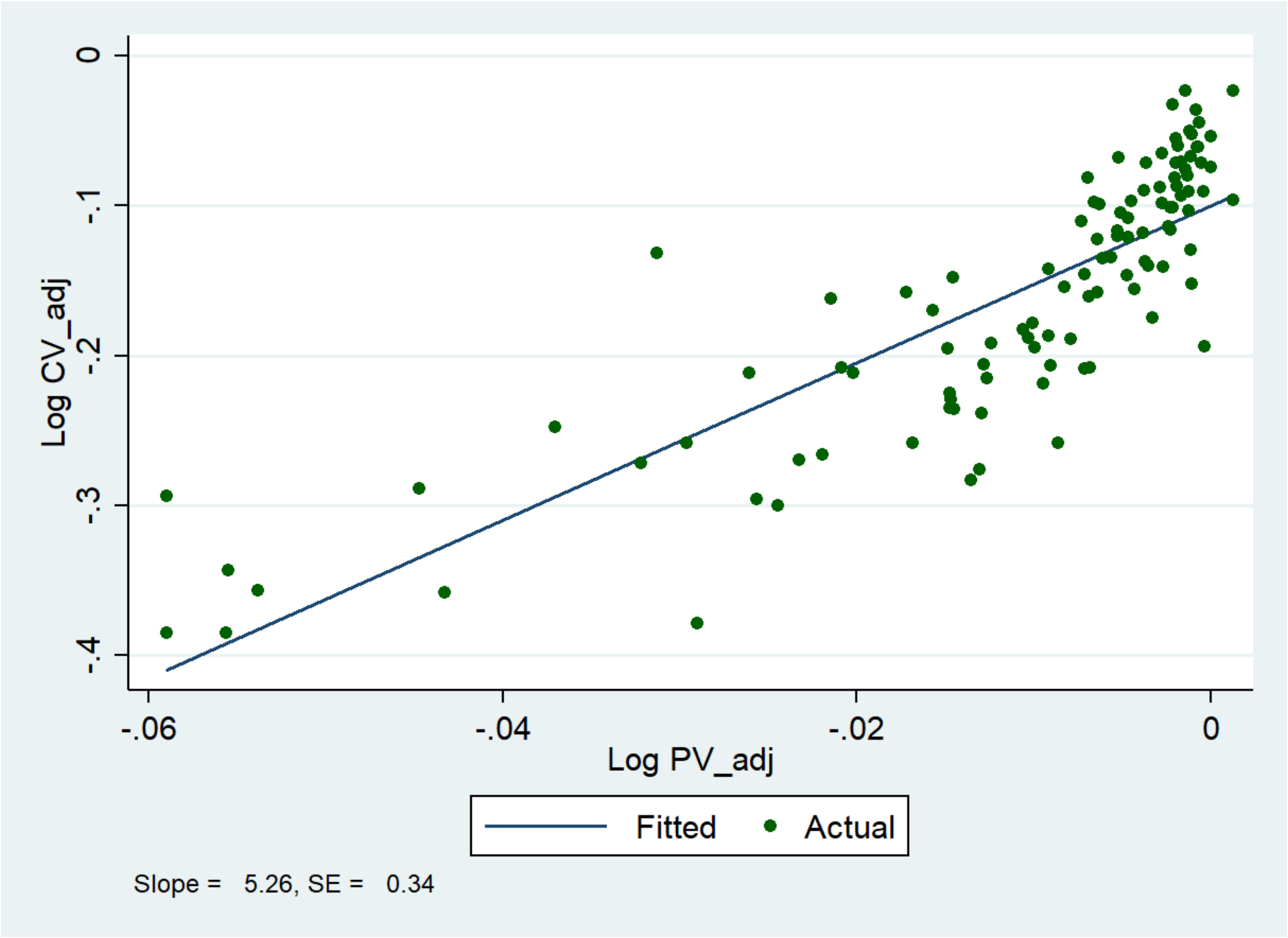
Alternative Price Indices Memory Cards



Correlations with UPI	Laspeyres	Feenstra	Hedonic (Laspeyres)	Hedonic (Paasche)
	0.15	**0.07**	**0.32**	**0.48**

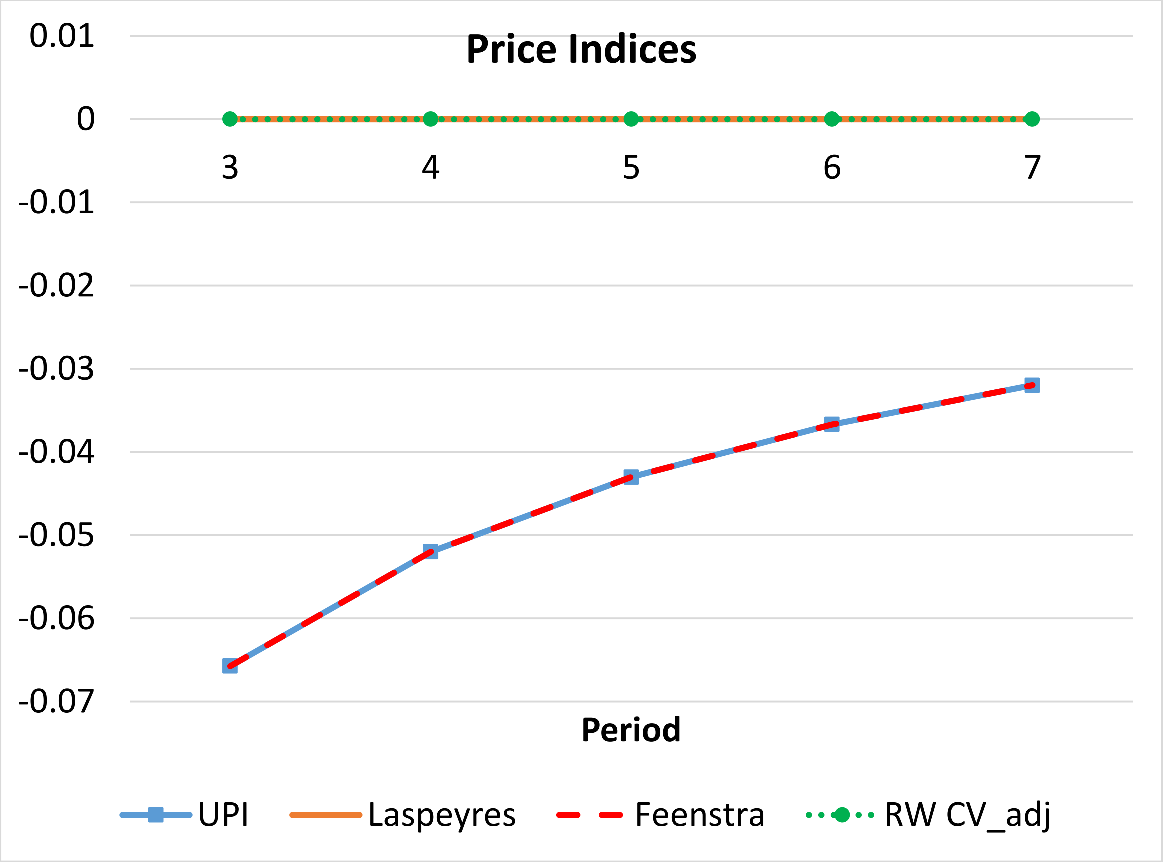
Key attributes for Memory Cards: Size and Speed, R-squared for Hedonics is about 0.8 each quarter

Empirically: Product Variety and Consumer Valuation Bias Correction Factors Positively Related



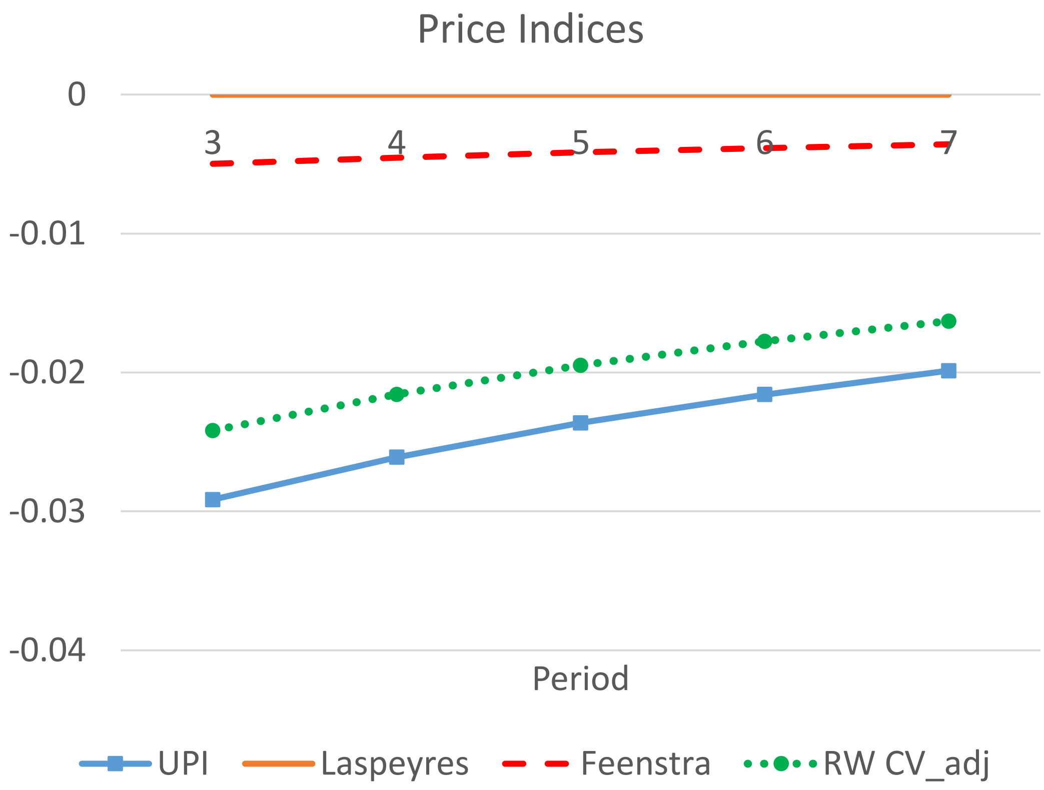
Source: Nielsen, Averages by Product Group

Why is Consumer Valuation Bias So Large? Simulated entry/exit with quality change



Simulation assumes no change in nominal prices. All changes in prices due to quality change

Why is Consumer Valuation Bias So Large? Simulated entry/exit with quality change



RW CV_adj dominates Feenstra adjustment with more gradual buildup/decline of product quality via entry and exit. Implies CV_adj may reflect dynamics of entry and exit

Open issues and challenges

Progress on conceptual and measurement methodology but open questions remain

- UPI: Nesting and estimation?
  - Use attributes for nesting?
  - Product appeal reflects relative demand residual
    - Specification/measurement error?
- Hedonics: Implementation at scale measuring attributes?
- Do these methods converge using the same attributes?

Extra Slides

Product Variety and Consumer Valuation Bias Adjustments

$$PV_{adj} = \frac{\lambda_{t,t-1}}{\lambda_{t-1,t}}$$

$$\lambda_{t,t-1} \equiv \frac{\sum_{k\in\Omega_{t,t-1}} P_{kt}C_{kt}}{\sum_{k\in\Omega_t} P_{kt}C_{kt}}$$

$$\lambda_{t-1,t} \equiv \frac{\sum_{k\in\Omega_{t,t-1}} P_{kt-1}C_{kt-1}}{\sum_{k\in\Omega_{t-1}} P_{kt-1}C_{kt-1}}$$

$$CV_{adj} = \left(\frac{\tilde{S}_t^*}{\tilde{S}_{t-1}^*}\right)$$

$\Omega_{t,t-1}$ = Goods common to t-1 and t

Ω_t= All goods in period t

$$S_{lt}^* \equiv \frac{P_{lt}C_{lt}}{\sum_{k\in\Omega_{t,t-1}} P_{kt}C_{kt}}$$

$$\tilde{S}_t^* = \left(\prod_{k\in\Omega_{t,t-1}} S_{lt}^*\right)^{1/N_{t,t-1}}$$

PV_{adj} and CV_{adj} may be related by complex post-entry and pre-exit dynamics

Unified Price Index (UPI) (Redding and Weinstein 2018)

$$\text{UPI} = {PV_{adj}}^{\frac{1}{\sigma-1}} \; {CV_{adj}}^{\frac{1}{\sigma-1}} \; \text{RPI}$$

PV_{adj} = Product Variety Adjustment (Feenstra)
CV_{adj} = Consumer Valuation Adjustment (RW)
RPI = Continuing goods price index (Jevons)

σ = Elasticity of substitution

Applied to narrow product groups; requires estimate of elasticity of substitution

Hedonics and transactions data

Following Pakes (2003) and Bajari and Benkard (2005) hedonics regressions estimated every period using item-level data

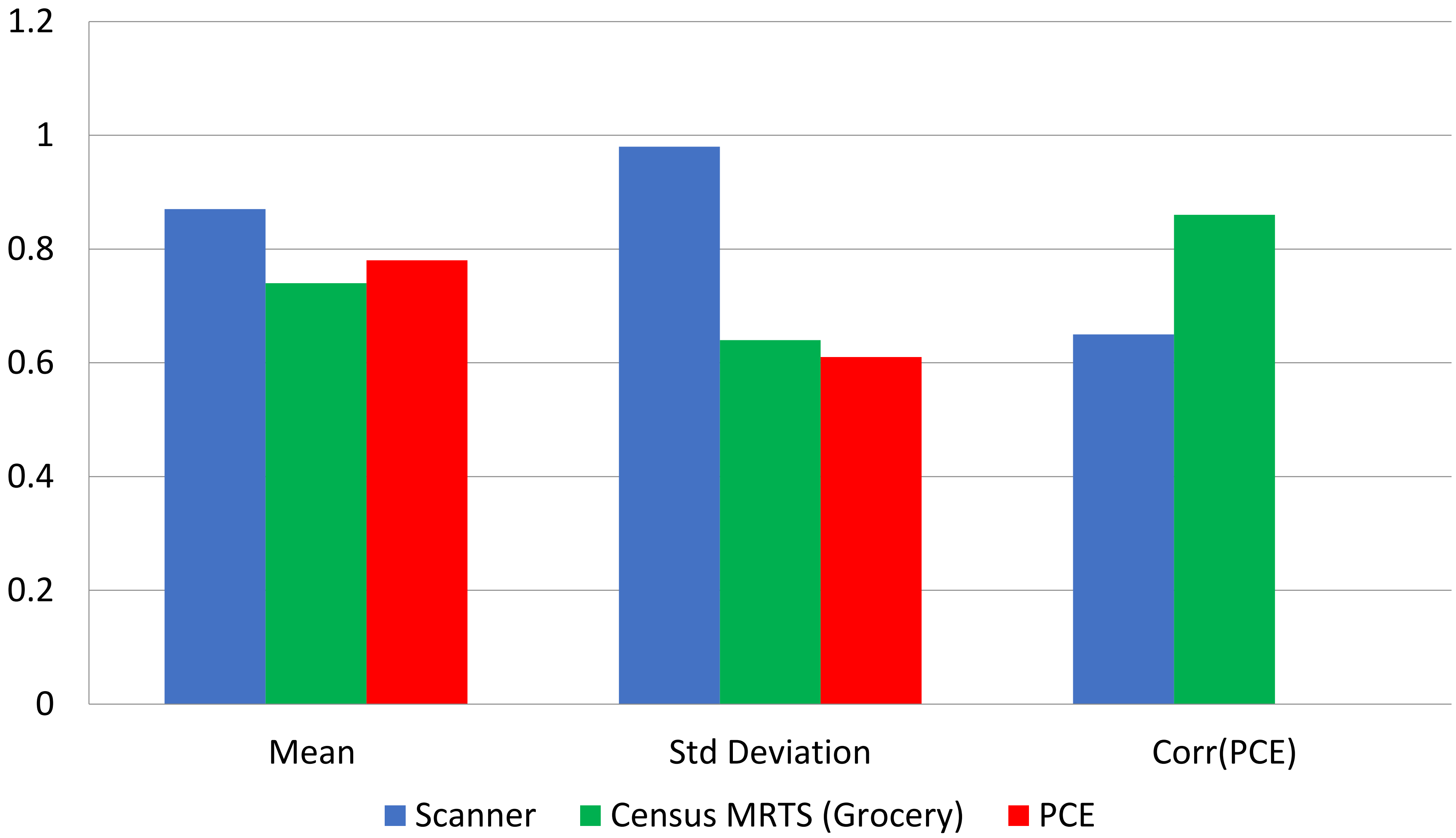
$$p_{it} = X_i'\beta_t + \eta_{it}, \text{ where } X_i \text{ is vector of characteristics}$$

Laspeyres Hedonic Index (*LPH*) given by

$$LPH_t = \frac{\sum_{i \epsilon A_{it-1}} h^t(X_i) q_{it-1}}{\sum_{i \epsilon A_{it-1}} h^{t-1}(X_i) q_{it-1}}$$

where $h^t(X_i)$ is the period *t* estimate of the hedonic function and A_{it-1} is the set of all goods sold in period t-1 (including exits).

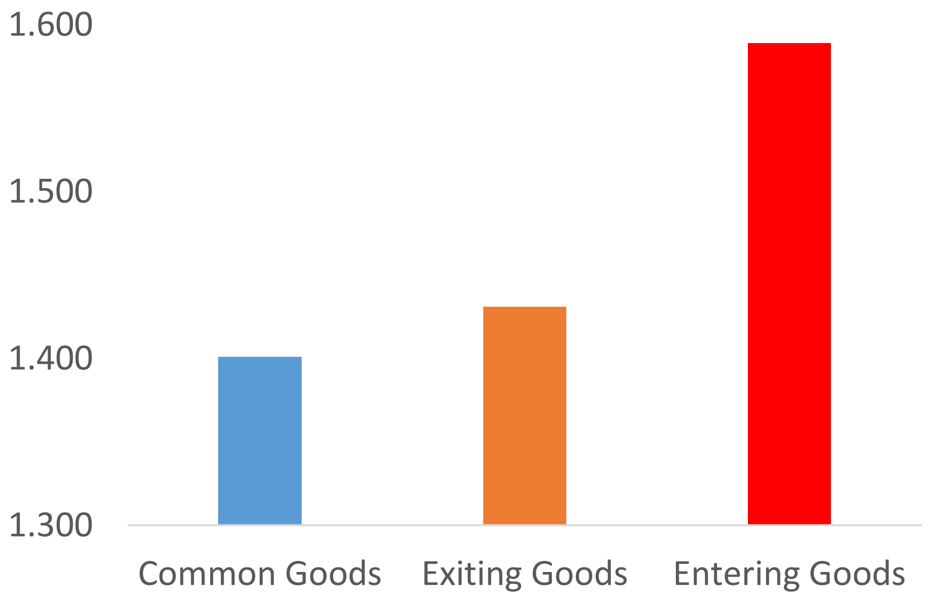
Growth Rates of Survey vs. Scanner Data of Sales Track Each Other Well: Food



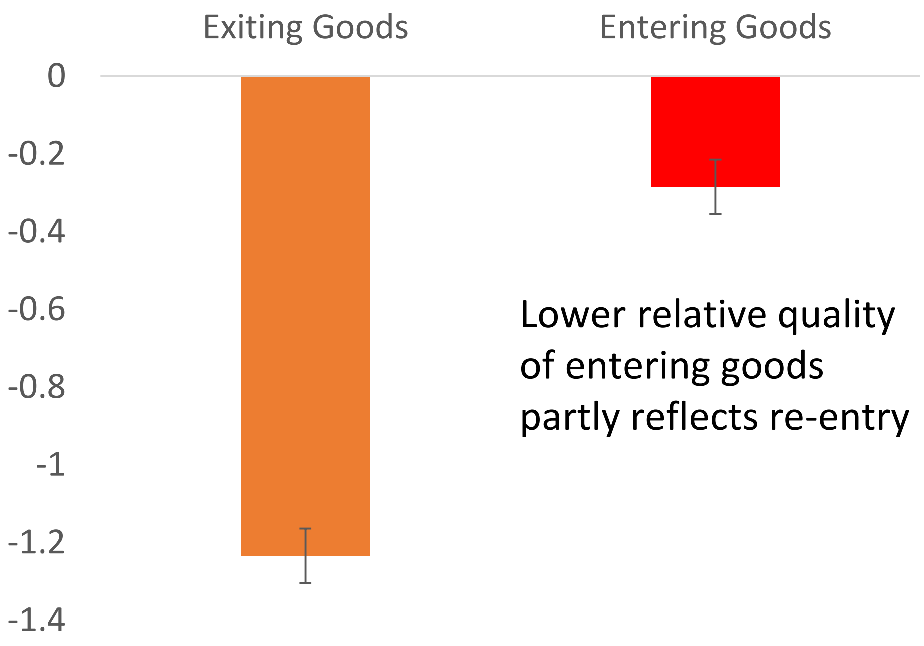
Scanner = Nielsen Retail Scanner, PCE = Personal Consumption Expenditures (Food), MRTS=Monthly Retail Trade Survey
Seasonally adjusted, quarterly nominal sales growth.

CES model can be estimated and UPI constructed for memory cards

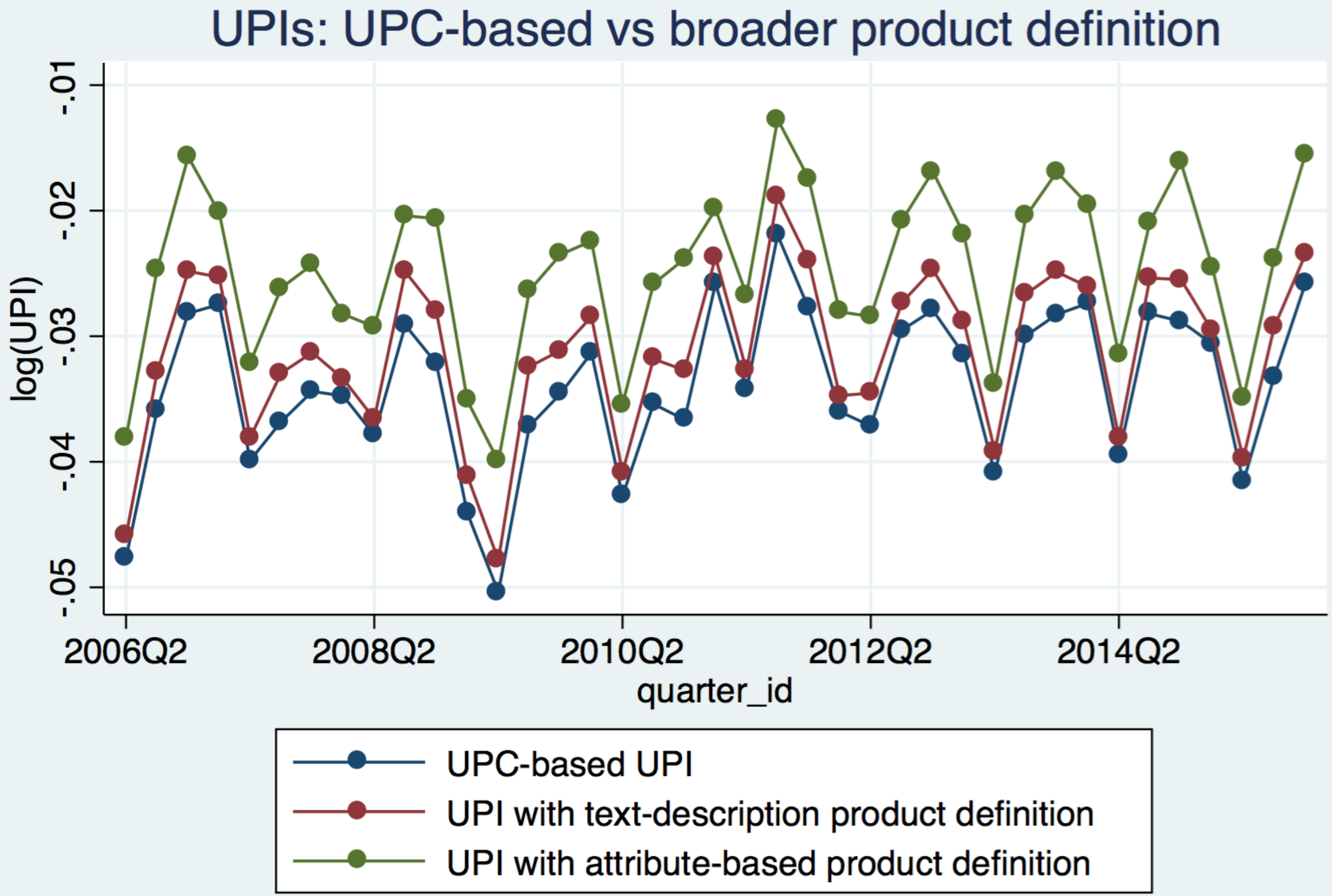
- Estimate of elasticity of substitution = 4.21 (0.48) (Feenstra method)
- Summary Statistics on product quality across items:



Std Deviation of Product Quality: Much higher across Entering goods



Average (relative) product quality much lower for exiting compared to entering goods



Notes: Quarter uses NRF definition, i.e. 2007Q1 refers to Feb 2007 - April 2007.

Item-level data shows that collapsing into broader product definitions increases UPI (towards Laspeyres)

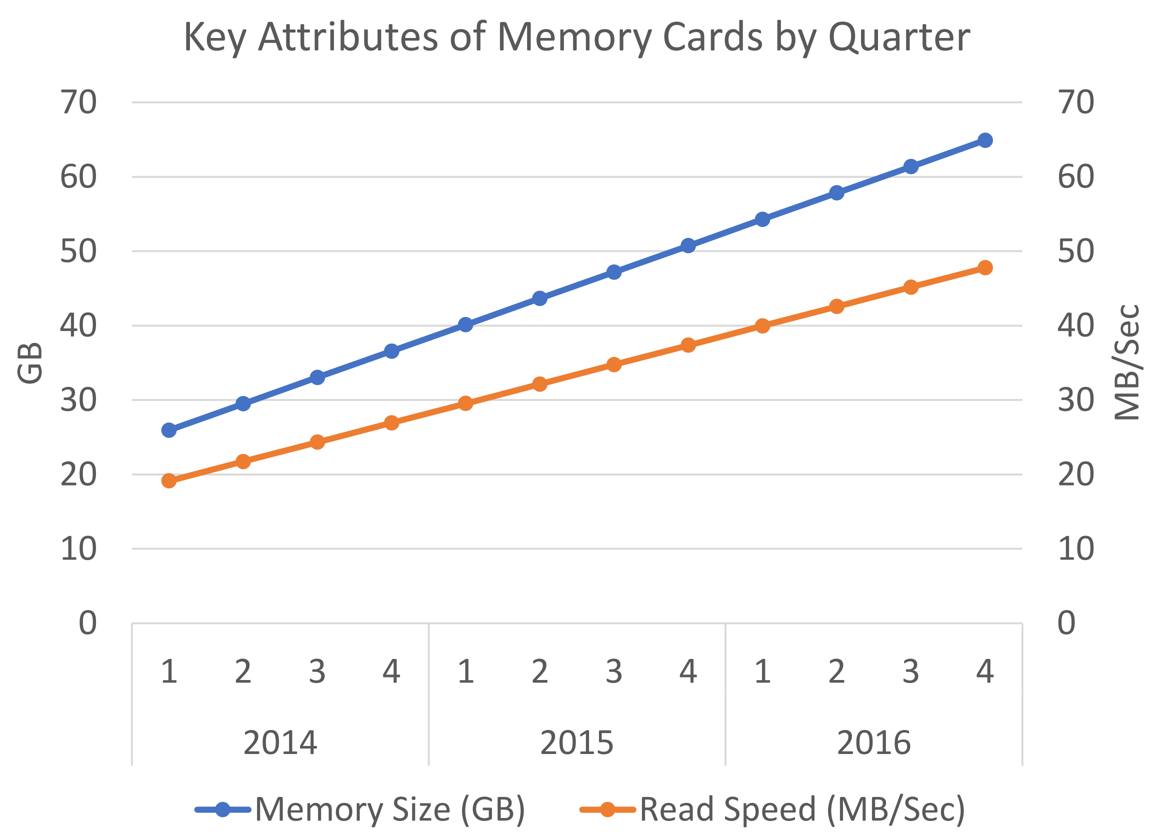
Attributes here based on product module, brand, size and packaging.

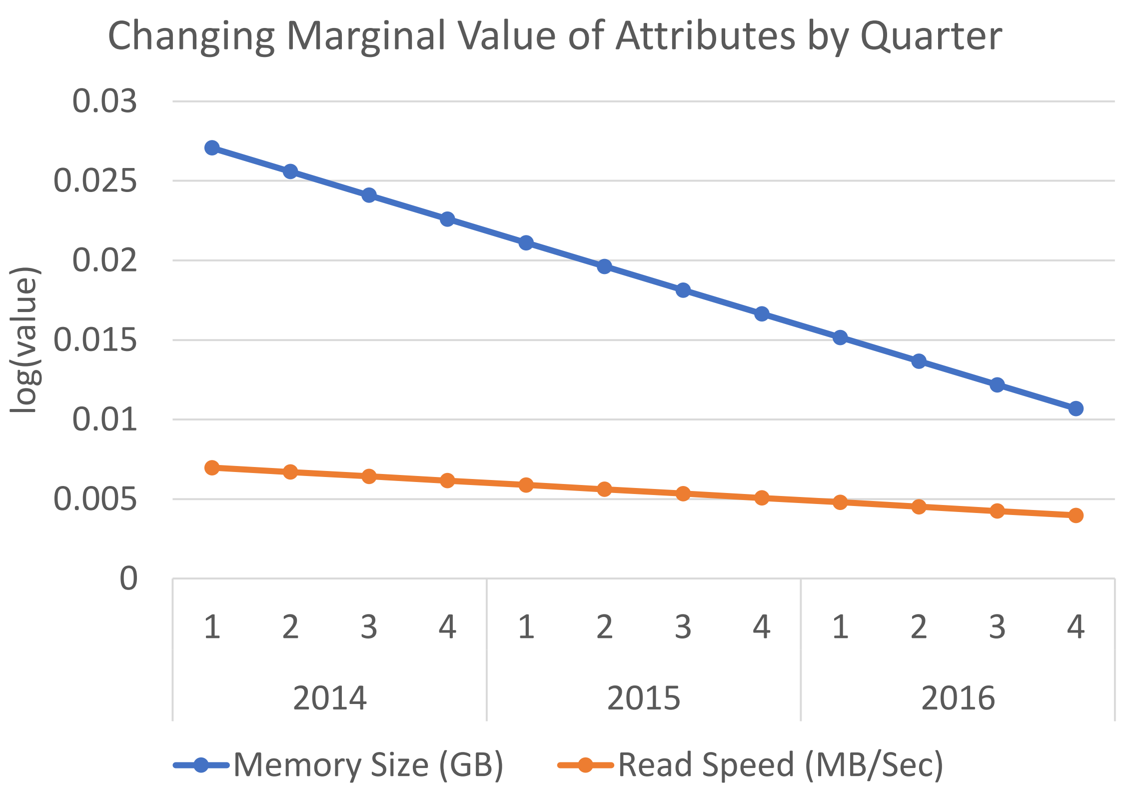
This approach could be Modified to nested CES.

More generally, close substitutes in terms of grouping of goods based on attributes is worth considering.

If attributes used to nest, do we converge towards Hedonics?

NPD item-level characteristics for Memory Cards
Quality improves over period; marginal value falls





Linear trend on sales-weighted Memory size and speed.

Trend of linear terms from hedonic regression

UPI vs. Hedonics?

Is UPI more general and scalable?

- Needs classification/nesting
  - Nests based on attributes likely the most appropriate approach
- Captures residual of relative demand curve?
  - Do we want residual? Specification/measurement error?

Are the magnitudes of the UPI plausible?

- Large magnitude of UPI due to consumer valuation (CV).